COMPARATIVE ANALYSIS BETWEEN VAR METHODS USED IN ECONOMIC STUDIES

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Abstract

In this article the authors have studied a wide bibliography aiming to make a comparative analysis between the VaR methods that are used in market studies, in particular but also in economic studies in particular.

The available data provided the possibility of a comparative analysis between the different variants of the VaR method, resulting in advantages or disadvantages for some of the relationships, but at the same time ensuring some deficiencies that can be avoided if this method is used in economic studies. . Of course, the VaR method is an old one, with multiple applications, but it remains relevant because it can be adapted to some specific conditions that the economy in general, the financial market or the market in general.

From the data available to them, the authors were able to suggest the possibilities of efficient use of different VaR methods, so that economic studies are carried out correctly, and the conclusions useful for their purpose of decisions in the macroeconomic system.

Keywords: *statistical methods, tests, estimates, risk, portfolios.*

JEL Classification: C13, G11.

Introduction

In the article Comparative analysis between VaR methods used in economic studies, the authors addressed a comparative analysis of the methods that are used in market studies. Thus, the different variants of the VaR method were analyzed one by one in order to highlight the advantages and disadvantages of this method in terms of statistical-econometric analyzes at macroeconomic level.

In a first stage, the historical simulation method was approached, which is easy to use given that there are sufficient data related to risk factors. Next, the parametric method and the Monte Carlo method are approached, which may not adequately describe the risk distributions of the factors. In particular, in the case of the Monte Carlo simulation method, the statistical distribution for risk factors can be selected.

In the study undertaken, given the limitations of the VaR method, alternative methods of analysis were considered that involve the use of the CAPM model, in which case the systematic risk of a portfolio or the CVaR risk measurement method can be estimated, which can be applied. and in problems involving leaping distributions.

Literature review

Angelelli, Mansini and Speranza (2008) studied two linear programming models used in portfolio selection, when transaction costs are also taken into account. Anghel, Anghelache, Niță and Bodo (2017) analyzed a series of aspects related to the Dvar system. Anghelache (2016) highlighted the importance of using econometric models in economic analysis. Banbura, Giannone and Reichlin (2010), as well as Sims (2012) addressed notions of the autoregressive vector methodology and its applicability on financial markets. A similar theme is studied by Carriero, Clark and Marcellino (2011). Bardsen, Nymagen and Jansen (2005) presented the role and applicability of macroeconomic modeling. Guidolin and Hyde (2010) conducted research to identify whether and how simple VARs can produce empirical portfolio rules similar to those obtained in a number of Markov multivariate models. Kilian and Murphy (2012) showed that sign constraints are not sufficient to deduce real price responses in financial markets. Kuzin, Marcellino and Schumacher (2011) performed a comparative analysis of MIDAS and VAR models with mixed frequency. Levy (2004) highlighted elements regarding cointegration.

Methodology, data, discussions, results

Analyzing the three VaR methods the obvious question is: which VaR calculation method is the best? Unfortunately, there is no simple answer. However, the strengths and weaknesses of each approach should be understood when making a decision. Different VaR calculation methods differ in their ability to capture the risks of options and similar instruments, flexibility in analyzing the effects of changes on assumptions, ease of implementation, ease of explaining to the Executive Management the financial situation at the end of a trading day and reliability of results. The best choice will be determined by how the risk manager considers it appropriate.

The two simulation methods work well, regardless of the presence of options and similar tools in the portfolio. In contrast, the parametric method is less able to capture such risks compared to the two simulation methods. The limitation of the parametric method is given by the fact that it incorporates options by replacing them with their mapping to delta-equivalent spot positions, ie by using linear approximations. For instruments or portfolios with a large amount of content in the form of options, linear approximations may not adequately reflect how the values of options change with changes in risk factors, especially over longer periods of time.

In contrast, simulation methods do not face such a problem, whether or not there are options in the portfolio, as they recalculate the value of the portfolio for each change in risk factors. In this respect, they estimate the correct distribution of the value of the portfolio. The distribution of the value of the portfolio generated by the Monte Carlo simulation depends on the statistical distribution established for the analysis of the evolution of risk factors and on the estimates of its parameters, both of which can be wrong and therefore lead to errors in the VaR calculation. Similarly, the distribution of the portfolio value generated by the historical simulation method can be misleading, if the previous N periods, from which a historical sample was constructed, were not representative.

When VaR was first developed, the parametric approach was considered the standard approach, because it is extremely efficient in terms of calculation. Efficiency results from the fact that this is an exact approach, which directly calculates a solution, rather than alternative approaches that determine a solution through iterative simulations of potential scenarios.

The historical simulation method is easy to implement when past values of risk factors are available. This is conceptually simple and can be implemented

The analysis of the methodologies for quantifying market risk in a roadmap. The main difficulty in implementing the historical simulation method is that it requires the user to have a set of relevant risk factors covering the last N days or periods.

In the case of the Monte Carlo simulation method, performing the simulations is not difficult, as the functions for generating random numbers are available as add-ins in Microsoft Office spreadsheets. However, selecting the type of distribution and selecting or estimating parameters requires high degrees of expertise and determination. Another disadvantage of the Monte Carlo simulation method is that it can be very time consuming for large portfolios.

In the presence of options and similar instruments in the portfolio, all three methods require pricing models to be available for these instruments. While the parametric method does not directly use instrument prices, options are mapped to their delta-equivalent positions and delta calculation requires valuation models. The need for valuation models can be a problem for portfolios that include certain exotic options or other products with complex integrated options.

The conceptual simplicity of the historical simulation method makes it easier to explain to the Executive Management. The parametric method is difficult to explain to an audience without technical knowledge in the field, because the use of normal distribution mathematics to calculate the standard deviation and VaR portfolio is simply a black box. The Monte Carlo method is even harder to explain. The key stages in the process of choosing a statistical distribution in order to be able to represent the changes in the values of the market factors and the generation of random samples are simply foreign to most people.

• All methods are based on historical data. Historical simulation is unique in that it is based so directly on historical data. One danger in this regard is that price changes over the last 100 days (or any other period) may have occurred on days that may not be typical. For example, if there has been a period of low volatility in market prices over the last 100 days, the calculated VaR, using historical simulation, could underestimate the risks of the portfolio. Other methodologies use historical data to estimate distribution parameters (e.g., the parametric method relies on historical data to estimate standard deviation and correlations of a multi-varied normal distribution of changes in market factors) and are also subject to the problem that the historical period used may not have been representative.

The parametric and Monte Carlo methods share another potential problem: assumed distributions may not adequately describe factor risk distributions. In general, the actual distribution of changes in market prices has extreme values in relation to the Normal distribution. Therefore, there are several different mean appearances than those predicted by a normal distribution. However, the Normal distribution for the parametric method seems to be a reasonable approximation for the calculation of VaR for efficient markets or index-linked portfolios.

A unique aspect in the case of the Monte Carlo simulation method results from the fact that the person responsible for building the model can select the statistical distribution for the risk factors. This flexibility allows the model designer to make a bad choice, in the sense that the chosen distribution does not adequately approximate the actual distribution of risk factors.

Regarding the collection of a sample of VaR amounts, the marked profits and losses of the portfolio answer two questions. First, does the distribution of profits and losses marked on the market appear to be similar to the distribution used to determine the amount of VaR? And second, do the actual losses exceed the VaR value with the expected frequency?

A limitation of this validation approach refers to the fact that the chances of occurrence will almost always be the cause that the distribution of profits and losses of the current portfolio differs somewhat from the expected distribution. For this reason, reliable conclusions about the quality of VaR estimates can only be made by comparing large samples of VaR amounts and actual changes in portfolio value. If such validation is considered essential, a period of time should be used to calculate VaR amounts, as it will take a long time to collect a large sample of monthly or quarterly VaR amounts, as well as portfolio gains and losses.

• In some situations, the risk manager may have reason to consider that historical standard deviations and / or correlations are not reasonable estimates for future periods. How easy can the VaR risk manager calculate in a what-if scenario, using each of the three methods? The historical simulation is directly connected by the historical changes of the risk factors. As a result, there is no natural way to perform this type of analysis. Instead, it is very easy to perform in the parametric method and the Monte Carlo method. In these two methods, historical data are used to estimate the statistical distribution parameters of changes in market factors.

• First, VaR can be used as a measure to help in the decision-making process. Thus, it provides a relevant analysis of the future evolutions of a portfolio according to market risks. In order to maximize the benefits of having a VaR analysis system, it should be used not only as a risk analysis measure, but also as an information measure, which helps in decision making. A great advantage of VaR is that it offers the possibility to compare several risks and, therefore, brokers have the chance to decide which option is more appropriate, given their preferences.

Second, VaR is a good tool for determining how risk-based capital allocation should be achieved by setting limit VaR positions. By introducing these positions, a better allocation of capital will be made within the financial intermediary in order to hedge against risks. The level at which the limit is set represents the capital allocation that reflects the risk appetite of the broker, taking into account the total level of risk tolerance of the brokerage company.

Setting limit positions involves some advantages:

- VaR limit position is dynamic. This encompasses both the circumstances of the general change in the market and the change in the composition of the portfolio per unit;
- VaR boundaries are easy to communicate at different levels of the organization, providing a good idea for management of how much can be lost in the case of any special unit;
- VaR may include leverage;
- VaR allows the integration of risks in different markets and instruments, and therefore provides a comprehensive picture of risk, even for non-homogeneous units;

- VaR can incorporate the effects of diversification into the portfolio;
- VaR limits can be set at different hierarchical levels of the organization and therefore risks can be managed both globally and on individual units. Due to the fact that they take into account the interactions between the different units within the financial intermediary, the limits do not have to be additive and can incorporate diversification effects.

VaR can also be used as a tool to measure performance, as it offers the possibility to compare different risky activities..

• Despite its benefits, VaR is not a flawless measure of risk. As a statistical measure for risk assessment, VaR can give a misleading impression as to the degree of relative risk: there could be two positions with VaR equal to a certain level of confidence and as a holding period, and yet a single position could involve loss of extreme values higher than the others. The VaR measure, taken individually, would incorrectly suggest that both positions were equally risky.

It is well known that the VaR method has the following disadvantages:

- It follows from the definition that VaR at the confidence level does not provide any information on the magnitude of losses occurring at a probability less than α;
- VaR does not respect the property of sub-additivity;
- Because VaR is not convex, optimization problems with VaR constraints can be difficult to solve numerically.

In addition, the implementation of a VaR system can sometimes be very resource consuming, both in terms of software and staff. Depending on the complexity of the instruments in the portfolio and the availability of data, the calculation can be performed and processed intensively, as a lot of information is required on a regular basis on the situation of the institution’s portfolio at any time and of the markets. However, once the benefits of implementing VaR begin to emerge, the method is seen more as having a positive effect.

• VaR limitations have highlighted the need for additional risk measures, because as can be seen, VaR is a statistical measure of market risk under normal conditions. But markets do not always behave as expected and unforeseen shocks can occur from time to time.

Thus, the stress test is used as an additional risk assessment measure. In measuring risk using the stress test method, it should be noted that extensive changes in risk factors are considered in order to reassess the portfolio and estimate the loss. The aim of this method is to provide a clear and objective measure of risk that can be easily understood. For the stress test, a specific set of changes in risk factors is set and then the change in portfolio value is calculated.

Two other methods of risk measurement are scenario analysis and the CAPM method. The first method is similar to the stress test method in that both use specified changes in market risk factors and nonlinear models according to which the change in portfolio value is then calculated. Unlike the previous method, in the scenario analysis the changes of the risk factors are determined taking into account the macroeconomic environment. Each of the 5-10 scenarios chosen corresponds to a certain type of market crisis and are built on the basis of historical data, on the basis of the current portfolio or according to the opinions of risk management experts.

The second alternative approach involves the use of the CAPM model (or a multifactorial model). The basic hypothesis of the CAPM model is that the return on shares of financial intermediary k, R_k is related to the market return by the following equation:

$$R_k = \alpha_k + \beta_k R_m + \varepsilon_k \tag{1}$$

where: α_k represents an intermediate-specific constant

β_k the market-specific component of the intermediary's return on shares

ε_k random element specific to the intermediary, not correlated with the evolution of the market

The decomposition of the variance of the intermediary's yields is given by:

$$\sigma_k^2 = \beta_k^2 \sigma_m^2 + \sigma_{k,s}^2 \tag{2}$$

where: σ_k^2 represents the total variance of the action yield

σ_m^2 - variance of the market yields

$\sigma_{k,s}^2$ - the variance of the intermediate-specific component, ε_k, or the intermediate *k*.

The variance of the yield of the intermediate therefore consists of a specific component of the market, $\beta_k^2 \sigma_m^2$ and a component specific to the intermediate $\sigma_{k,s}^2$.

Taking into account the fact that the yields of the intermediary are normally distributed with zero mean, the VaR of a position on shares of the intermediary k, evaluated at x_k is::

$$VaR = -Z_\alpha \sigma_k x_k \tag{3}$$

When aggregating risk for a diversified portfolio, a key role in calculating total risk is the market risk component, $\beta_k^2 \sigma_m^2$.

Given that the specific risk associated with each position is assumed to be uncorrelated with both market performance and other specific risks, the share of total risk due to specific risk factors is continuously reduced as the portfolio becomes more diversified. and approaches zero as the portfolio approximates market composition.

Thus, estimating only the systematic risk of a portfolio using the CAPM approach is reduced to a mapping process. Therefore, assuming that the portfolio consists of N positions on separate assets, with market values x_k for k = 1, 2,…, N and considering that the beta factors of the positions are β_k, for k =l,2,...,N and the volatility of market returns is σ_m, the systematic aggregate VaR of the portfolio is:

$$VaR = -Z_\alpha \sigma_m \sum_{k=1}^{N} \beta_k x_k \quad (4)$$

Thus, the systematic VaR represents the product between the critical value, the market volatility and the weighted amount depending on the beta of the positions in shares. If the total market value of the portfolio is denoted by X, the above equation can be written:

$$VaR = -Z_\alpha X \sigma_m \sum_{k=1}^{N} \frac{\beta_k x_k}{X} \quad (5)$$

where

$$\sum_{k=1}^{N} \frac{\beta_k x_k}{X}, \quad (6)$$

represents *the beta* portfolio

An alternative method to the VaR method of risk measurement is Conditional VaR (CVaR). This is the average value of losses higher than the VaR for a given asset. The CVaR risk measurement method, with a minor change, can also be applied in problems involving jump distributions. We also know that CVaR is a coherent risk management measure, which has many attractive properties, including convexity. In addition, a lower CVaR implies a portfolio with a lower VaR.

For the calculation of the optimal CVaR, an optimization problem is proposed. When the optimization problem is approximated by a Monte Carlo simulation, it is equivalent to a linear programming (PL) problem and can be solved by a standard PL method. More specifically, they showed that the problem of optimizing CVaR / VaR portfolios has an infinite number of solutions in the case of portfolios with derivative contracts, if the value of the contracts is calculated using delta-gamma approximations. in particular, the optimal portfolio extends to a space of size (*n* - *(2d* + 3)) where n is the total number of instruments in which one can invest, and d is the total number of risk factors, even in the situation in which the value of the derivative contract depends on several risk factors.

When the values of derivative contracts are calculated by methods that involve the use of analytical formulas, partial differential equations or the Monte Carlo method, the CVaR / VaR optimization problem for derivative product portfolios remains poorly represented, in the sense that many portfolios have CVaR / VaR values. similar to that of the optimal portfolio and a slight disruption of the data can lead to significantly different solutions from optimal solutions.

Thus, for a time horizon t and a confidence level α, the CVaR is the conditional expected loss at a level above that given by VaR for the time horizon *t* and the confidence level α.

To analyze VaR, it can be defined mathematically as:

$$VaR = S_\alpha(\xi) = inf\{\xi / P(\xi \leq S) \geq \alpha\} \tag{7}$$

Where α is the confidence level and ξ is a random variable

CVaR can be defined mathematically as follows::

$$CVaR = E[\xi / \xi \geq S_\alpha(\xi)] = E[\xi / \xi \geq VaR] \tag{8}$$

Where ξ is a random variable.

From this definition it follows that CVaR> VaR. Therefore CVaR cannot be underestimated. Unlike VaR, CVaR is convex and coherent, in the sense that it respects the sub-additivity property and is monotonous. This means that the CVaR function will be easier to optimize in an optimization problem that aims at a robust distribution between assets, within a portfolio. If we assume that the return follows a normal distribution, the CVaR value for a portfolio will be:

$$Cvar = \mu + k_1(\alpha)\sigma \tag{9}$$

provided that:

$$k_1(\alpha) = \frac{1}{\sqrt{2\pi}\, e^{[erf^{-1}(2\alpha-1)]^2}(1-\alpha)} \tag{10}$$

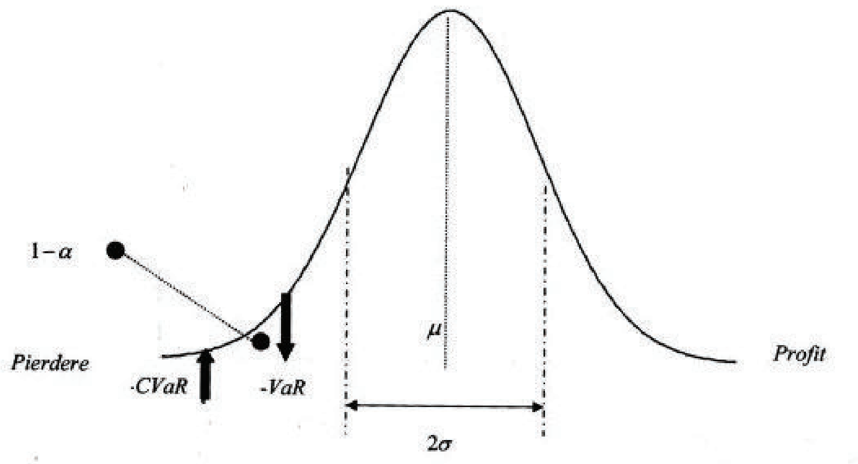
$$erf(z) = \frac{2}{\sqrt{\pi}} \int_0^z e^{-t^2}\, dt \tag{11}$$

However, before using a parametric approach, the CVaR can also be calculated empirically. As in the case of VaR, using historical or stochastic simulations, future prices can be generated and the CVaR calculated.

From Figure 1 it can be seen that the CVaR is in the distribution queue, beyond the VaR value of the portfolio. Therefore, a distribution of extreme events can be used to formulate CVaR, regardless of profit distributions.

Distribution of the profitability of a portfolio

Figure 1



Because CVaR is the average loss greater than VaR, a distribution of extreme values will be used to define CVaR, according to the relation:

$$CVaR_{\alpha}(x,\varsigma) = \varsigma + (1-\alpha)^{-1}\int_{\xi \in R^n}[f(x,\xi) - \varsigma]^{+}p(\xi)d\xi \qquad (12)$$

where: α is the level of confidence

ς the VaR for the portfolio

x is a vector that measures the share of assets in the portfolio

ξ is a random variable

$p(\xi)$ is the distribution density of ξ

$f(x,\xi)$ is the loss function for the portfolio

$z^{+} = max\{z,0\}$

$[f(x,\xi) - \varsigma]^{+}$ is defined as $[f(x,\xi) - \varsigma]^{+} = \begin{cases} f(x,\xi)\ daca\ f(x,\xi) - \varsigma > 0 \\ 0, altfel \end{cases}$

The CVaR calculation process can be reduced to a PL problem so that the integral for continuous distribution can be estimated using scenarios:

$$\xi \rightarrow \xi^{s}, p(\xi) \rightarrow p_s, \sum_{s=1}^{S} p_s = 1, f(x,\xi) \rightarrow f(x,\xi^{s}) \qquad (13)$$

Transforming CVaR's definition as follows:

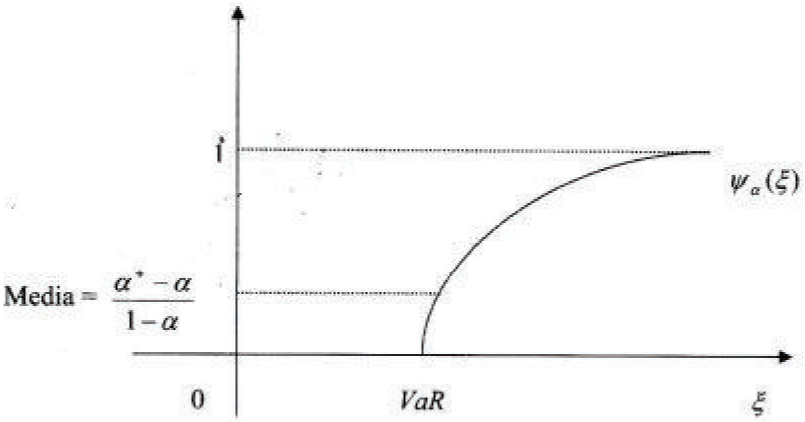
$$CVaR_{\alpha}(x,\varsigma) = \varsigma + (1-\alpha)^{-1}\sum_{s=1}^{S}[f(x,\xi^{s}) - \varsigma]^{+}p_s \qquad (14)$$

This definition can be reduced to a PL problem by extending $[f(x,\xi^{s}) - \varsigma]^{+}$ as follows:

$$[f(x,\xi^s) - \varsigma]^+ \to z_s \geq f(x,\xi^s) - \varsigma;\ z_s \geq 0;\ \ s = 1 \ldots S$$

Distribution of extreme values for a level α, $\psi_\alpha(\xi)$

Figure 2



Therefore, this linear formulation is guaranteed by the implementation of the z + function when, for all s, zs is minimal. Thus, the meaning of CVaR is made clearer with this formulation. As can be seen z_s will be zero in all cases where the portfolio loss is less than the portfolio VaR. If the loss is greater than the portfolio VaR, z_s will be given by the difference between the loss and the portfolio VaR. Given that the z_s distribution represents the distribution of extreme values of losses exceeding VaR, the average can be calculated by dividing the weighted sum of z_s by (1 - α). Thus, the portfolio CVaR is therefore this average value added to the portfolio VaR.

Since CVaR> VaR, if the asset weights are optimized in such a way that for all s, zs is equal to zero, the optimal CVaR = VaR and S will be equal to the portfolio VaR. This linear formulation is extremely beneficial, as it means that large portfolios can be built and optimized with a CVaR constraint in a faster time.

Using the CVaR definition and the optimization problem, two optimization problems result. First of all, the loss can be minimized with a CVaR constraint for the portfolio, as follows:

$$\min_{x,\varsigma} \frac{1}{\sum_{i=1}^{n} q_i x_i^0} \sum_{i=1}^{n} -E(\xi) x_i \tag{15}$$

With the following conditions:

$$\varsigma + \frac{1}{(1-\alpha)S}\sum_{s=1}^{S} z_s \le \eta \tag{16}$$

$$z_s \ge \sum_{i=1}^{n}(-\xi_i^s x_i + q_i x_i^0) - \varsigma;\ z_s \ge 0 \tag{17}$$

$$\sum_{i=1}^{n} q_i x_i^0 = \sum_{i=1}^{n} c_i q_i(\underline{\delta}_i + \bar{\delta}_i) + \sum_{i=1}^{n} q_i x_i \tag{18}$$

$$x_i = x_i^0 - \underline{\delta}_i + \bar{\delta}_i \tag{19}$$

$$E(\xi_i)x_i \le \nu_i E(\xi_k)x_k \tag{20}$$

$$x_i \ge 0 \tag{21}$$

where: q_i is the initial price of asset i;
x_i^0 s the initial number of units held in asset i;
x_i is the number of units held in the asset at the end of the period;
$\underline{\delta}$ vector of shares sold from asset i;
$\bar{\delta}$ vector of units purchased from asset i;
ξ_i^s is the scenario that depends on the price of the asset at the end of the period;
S is the total number of scenarios constructed;
c_i is the transaction cost for asset i;
α is the confidence level;
ς is the VaR portfolio;
η is the upper limit for the CVaR portfolio;
ν_i is the maximum share that the asset can have in its portfolio;
x vector holding the weights of the assets within the portfolio.

The objective function (15) aims to minimize the loss of a portfolio. Inequalities (16) and (17) are CVaR constraints of the portfolio. Relation (16) assumes that the probability of occurrence of each scenario is the same. The inequalities (18) and (19) ensure that the transaction costs, proportional to the value of the traded shares, are taken into account when optimizing the portfolio. They add the necessary friction to the model so as to ensure that the sale or purchase of assets is not carried out without payment of a penalty. Inequality (20) is an established constraint to ensure a diversified portfolio. The constraint (21) ensures that short positions are not allowed.

Second, the CVaR for a portfolio can be minimized by applying profitability constraints as follows:

$$\min_{x,\varsigma}\left[\varsigma + \frac{1}{(1-\alpha)S}\sum_{1}^{S} z_s\right] \tag{22}$$

Provided that

$$\frac{1}{\sum_1^n q_i x_i^0}\sum_1^n -E(\xi)x_i \geq R \tag{23}$$

And the constraints (17), (18), (19), (20), (21) where R is the expected return.

The two minimum issues that have been presented aim at optimizing a portfolio by generating S scenarios for a future period. By increasing the number of scenarios, a financial intermediary is expected to obtain a more accurate value for VaR.

A variant for increasing the number of scenarios and generating a higher number of prices for the next period is to build an optimal problem over several periods.

Conclusions

From the study undertaken by the authors in the article *Comparative analysis between VaR methods used in economic studies*, a series of conclusions can be drawn, both theoretical and especially practical. Thus, a first conclusion that emerges is that the historical simulation method is an easy method to implement when past values of risk factors are available, but it is still necessary in such an analysis for the user to have a time series of relevant risk factors covering the last periods.

Another conclusion is that the reliability of the methods can be partially addressed by comparing the actual changes in the portfolio value of the VaR amounts, because the VaR approach explicitly specifies the probability that the actual losses will exceed the VaR value. Also, the CVaR risk measurement method, which is an alternative method of the VaR method and involves an optimization problem, which if approximated by a Monte Carlo simulation will be equivalent to a linear programming problem solvable with standard methods.

Last but not least, following the study, we can conclude that large portfolios can be built and optimized in a shorter time with a CVaR constraint. Loss can also be minimized with a CVaR constraint for a portfolio and CVaR for a portfolio can be minimized by applying profitability constraints.

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